Assessment and Optimization of Demand Response Technologies in the Smart Grid of Valverde, Évora

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Abstract

The following document presents a case study analysis of SENSIBLE, a demonstration project in Valverde, Portugal, led by EDP NEW R&D. The main goal is the integration of different storage technologies, photovoltaic energy and a Home Management System (HMS) into a total of 25 households, maximizing the economic benefits for the end customer.

The performance of the project is assessed from August 2017 to July 2018. Then, the HMS is modelled with Matlab to test some demand response strategies, based on day ahead forecasts on the photovoltaic production and the expected electricity demand.

From the analysis, the average Self-Consumption Ratio is 57.23%, and an average Self Sufficiency Ratio is 31.16%. The project generates on average 29 €/month of savings for each customer. From a financial perspective, the most feasible configuration is the installation of a photovoltaic panel with a smart water heater reaches the back in 12 years, with an IRR of 14%.

The model has successfully been implemented and tested on a specific customer to check the reasonability of the results. The application of the new algorithm on the Home Management System manages to shift the demand to night hours, but does not show potential in generating savings.

The carbon footprint of the end customers has been reduced of around 10.9 tonnes of CO_2 equivalent, due to the renewable penetration.

A final discussion on the potential development of such projects across Europe is then introduced, concerning the risk of an unfair redistribution of the grid costs.

Keywords: Demand Response, Smart Grids, Photovoltaic, Forecasts, Energy Storage

1 Introduction

The development of smart grids in the different countries and regions strongly needs a preliminary test of the business models, to adequate technology to the local realities. In this context, both small and large-scale pilot projects are necessary. A very interesting case study is given by SENSIBLE, led by Siemens Corporate Technology A.G and NEWR&D/ Labelec, EDP, and financed by the European Commission in the Euro 2020 Horizon. SENSIBLE is a demonstration project, with the main goal of integrating different storage technologies, micro-generation and renewable energy into power networks, homes and buildings. The project investigates the possibility to generate value not only for the grid operator, but also for the end customers. SENSIBLE is running in parallel in the three locations: Evora, Nottingham and Nuremberg. The specific goal of the installation in Evora is to maximize the self-consumption of photovoltaic energy, and to optimize the system from the perspective of the end customer.

1.1 Project description

A total of 25 customers has been monitored over one year: most of them are residential users, except for one small manufacturing company and a restaurant. The installed system is made by a Home Management System HMS, a photovoltaic panel of 1.5 kW, an inverter, an electric smart water heater (different capacity for each customer), and a battery with 3.3 kWh of capacity. The customers are metered every 15 minutes, all of them have the photovoltaic panel, the inverter and the HMS. Regarding the storage, they have different configurations:

- 10 have only the water heater;
- 9 have only the battery;
- 6 have both.

The time window for this work is between August 2017 and July 2018.

The current Home Management System manages the excess electricity from the pv according to the scheme in Figure 1, prioritizing the water heater over the battery and charging the latter only with solar energy and never with the grid.

Figure 1: HMS algorithm of excess electricity management

Nevertheless, the water heater is subject to considerable thermal losses, and the battery is often underused during winter month. On top of that, most of the customers are offered a bi-hourly tariff, where the price during off-peak hours is less than half of the price during peak.

1.2 Scope of the work

The primary scope of the work is to assess the performance of the equipment installed in the project starting from the analysis of the data available. The performance is assessed from the technical, economic and financial perspective: the effectiveness of the system in terms of self-consuming the solar energy and to match it with the demand, the savings generated by the project and the investment analysis in a long-term time horizon.

The secondary scope of the work is to create a Matlab model of the Home Management System to replicate in a realistic way the working principle of the current algorithm. After a validation of the model, the algorithm can be changed in the way the storage is dispatched, trying to increase the savings on the electricity bill of the end customer. The idea for this work is to make use of a weather forecasts methodology to predict solar radiation and photovoltaic generation, to increase the use of the battery when the photovoltaic generation is low and making use of the advantages of the tariff scheme.

2 Literature review

2.1 Smart grids applications

Smart grids are an infrastructure that connects electricity generation to end users, using advanced digital technologies to monitor and manage the power flows. The current centralized generation networks are struggling to adapt to the new variability and demand peaks. The introduction of smart grids allows an easier integration of distributed renewable generation. Worldwide, the interest and consequently the investments in smart grid technologies is growing. The growth between 2014 and 2016 accounts for 12% overall. In general, every year more than 10 billion of dollars are invested in the deployment of new technologies in the distribution networks as shown in Figure 2.

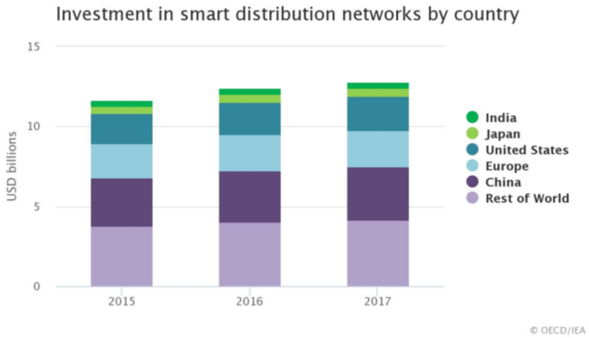

Figure 2: Investment in smart distribution networks by country [4]

2.2 Demand Response

Historically the grid balance has been achieved mainly by matching the demand in the different hours of the day by adapting the generation. For most of the 20th century, fossil fuels were the main energy source, and their flexibility has been used to supply electricity in a reliable and cheap way.

In the last years, solar and wind generation started to play a major role in the modern energy systems. The cost of new photovoltaic panels has decreased 70% since 2010, wind by 25% and batteries by 40%. [1]. With the introduction of variable and distributed generation of renewables, situations of overproduction happen when there is high availability of natural resources, like strong wind or high solar irradiation, and low demand. On the other hand, when renewables energy availability is low, demand needs still to be met with expensive and carbon-intensive fossil fuel-based generation.

Demand Side Response, or just Demand Response (DSR/DR) is a set of measures where the renewables, energy efficiency and electrification interact for the optimal operation of an energy system.

The innovation of DR is to exploit flexibility of the electricity demand to consume energy when naturally available. Consumers are contributing to the grid balance offering the possibility to adapt part of their demand to the renewable generation. The implementation of DR is a win-win situation: the grid operator more likely avoids supply disruptions or curtailments of renewable generation; the consumers can be paid to change their consumption patterns by shifting or reducing loads, or by offering flexible loads as fast frequency response measure.

The potential for DR worldwide is estimated to be around 4,000 TWh per year, about 15% of the total electricity demand. Flexible loads are mainly found in the commercial and industrial sector: large scale heating and cooling, water treatment and electric vehicles charge. In the residential sector a high level of technology for connection and automation is necessary, as well as a figure that can aggregate the customers and optimally manage their flexibility. The application of Demand Side Response requires not only the deployment of technology, but also an adequate policy framework. DSR finds the incentives in the market, where flexibility is priced and remunerated.

2.3 Weather forecast methodologies

Renewable generation potential is dependent on weather conditions. Forecasting solar irradiation or wind speed is extremely important when planning the dispatch [2]. The Clear Sky Persistence Model, described in detail in [3] is very simple, the assumption of the model is that the clear sky index of a certain time step persists for the following one.

$$K(t+\Delta t) = K(t) = \frac{GHI_{measured}(t)}{G_{clr}(t)} \qquad (1)$$

Where $K(t)$ is the clear sky index at the time step t, $GHI_{measured}(t)$ is the Global Horizontal Irradiance GHI measured at ground level, $GHI_{clr}(t)$ is the GHI for clear sky conditions.

The Solar Forecast Similarity Method is presented in [4]. It predicts the following day irradiance and irradiation by searching in a long-term radiation database the most similar days to the current one and extracting for each of them the following day. These days are then averaged to obtain a forecast. To detect the similar days, the criteria is the minimum of the square distance for each day. The algorithm works better for areas with very stable condition.

2.4 Radiation models and photovoltaic generation

The estimation of the photovoltaic generation requires technical information on the selected panel, and a physical model to project measurements of the GHI on a tilted surface. In [5] The Perez Radiation model is presented. The total radiation on the tilted surface is given by equation 2.

$$\begin{aligned} I_T = I_b R_b + I_d (1 - F_1)\left(\frac{1+\cos\beta}{2}\right) + I_d F_1 \frac{a}{b} \\ + I_d F_2 \sin\beta + I\rho_g\left(\frac{1-cos\beta}{2}\right) \end{aligned} \qquad (2)$$

Where I_b is the beam irradiation, I_d is the diffuse irradiation, β is the tilt angle, ρ_g is the reflectance, R_b is the ratio of beam radiation on a tilted surface to that of a horizontal surface, F_1 and F_2 are brightness coefficients. The coefficients a,b can be defined as:

$$a = \max(0, \cos\theta), \quad b = \max(\cos 85, \cos\theta_Z) \qquad (3)$$

Where θ is the incidence angle and θ_Z is the zenith angle. To calculate the photovoltaic electricity generation some parameters can be extracted from the technical details of the manufacturers, other can be calculated from the literature.

$$E_{pv} = I_T \cdot A_{pv} \cdot \mu_{module} \cdot \mu_T \cdot \mu_{dirt} \cdot \mu_{inv} \qquad (4)$$

Where A_{pv} is the panel area, μ_{module} is the module efficiency, μ_T is the efficiency due to the temperature, μ_{dirt} is a dirtiness coefficient, μ_{inv} is the inverter euro efficiency.

2.5 Domestic Hot Water DHW

Electric water heating in Portugal accounts for more than 5% of the annual residential electricity demand [6]. DHW usage depends on behavioural factors and on the number of people living in the house. Thermal energy can be stored more easily and in a cheaper way, partially dissociating the time where water is heated up and the time where it is consumed. In a variable price tariff scheme for electricity, this dissociation gives room for demand response applications. [7] Electric water heaters have a huge flexibility in terms of control, because they can be re-parameterizable, interruptible and shiftable. From [8] the energy balance of the water heater considering inlet and outlet temperatures is:

$$E_{wh,el} = \frac{V_{H2O} \cdot \rho_{H2O} \cdot c_{H2O}\,(T_{max} - T_{inlet})}{3600}\ [Wh_{el}] \qquad (5)$$

Where $V_{H20}[l]$ is the DHW demand, ρ_{H2O} is the water density assumed 1000 kg/m^3, c_{H2O} is the specific heat of water, assumed 4.186 J/(g °C).

3 Data preliminary analysis

3.1 Dataset details

The work is based on real data from the dataset provided by EDP. Before starting the performance analyses, the dataset has been checked and treated to improve the accuracy of the results, and consequently to derive meaningful models. The parameters available are:

- Battery input and battery output;
- Grid electricity purchase and injection;
- Photovoltaic generation;
- Water heater consumption;
- Water heater temperature;
- Battery temperature;
- Battery state of charge

In general, not all the customers have been metered for the same number of days. The dataset presents some frequent issues, hence not for all the customers a complete and accurate analysis can be performed.

3.2 Main variables

Some of the main variables, like the electric load, are secondary and derived from computations on the data. Three types of energy demand are identified:

- Thermal demand, or electricity stored in the water heater E_{wh};
- Total Electricity Demand of the customers, including thermal consumption E_{dtot};
- Electricity Demand excluding the water heater E_d, that means electric load of the appliances;

The total electricity demand is presented in equation 6:

$$\begin{aligned} E_{dtot} &= E_{b,out} - E_{b,in} + E_p - E_{inj} + E_{pv} \\ &= \Delta B + \Delta E_g + E_{pv} \end{aligned} \qquad (6)$$

ΔE_b is the balance of the battery, ΔE_g is the balance of the grid and E_{pv} is the electricity of the photovoltaic panel. The electricity demand excluding the domestic hot water includes all the other appliances, and it is obtained subtracting the water heater demand to the previous equation, to obtain equation 7:

$$E_d = \Delta E_b + \Delta E_g + E_{pv} - E_{wh} \qquad (7)$$

Theenergy balance is shown in Figure 3 for more clarity.

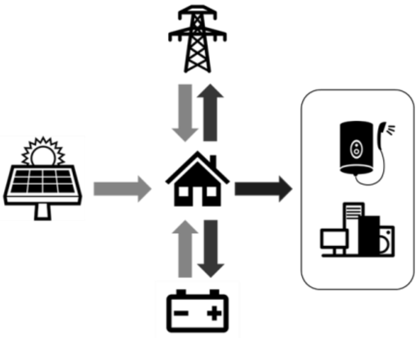

Figure 3: Energy balance of the house

4 Methodology

4.1 Customers analysis

One of the main variables from the dataset is the photovoltaic generation. The average production is 2.17 MWh/y. The capacity factor of each customer can be calculated from equation 8:

$$CF = \frac{E_y[\frac{kWh}{y}]}{P_r \cdot 8760} \qquad (8)$$

Where P_r is the rated power and E_y is the yearly electricity production. The average capacity factor is 16.51 %.

The electricity consumption has been estimated according to equation 6, and clustered according to the type of equipment installed. The results are presented in Figure 4.

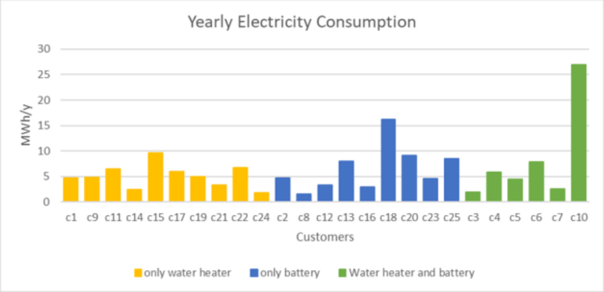

Figure 4: yearly electricity consumption clustered for the different installation configurations

The average electricity consumption per capita in Portugal is 4.85 MWh/y [9], in Valverde the average is 5.06 MWh/y if only the residential customers are considered, and 6.38 MWh/y if also the restaurant (customer 18) and the manufacturing company (customer 10) are included.

The domestic hot water consumption is expressed in terms of electricity input in the water heater. The values are shown in Figure 5 only for the customers having a data availability higher than 75%. The average share of the electric load dedicated to the water heater is 34%.

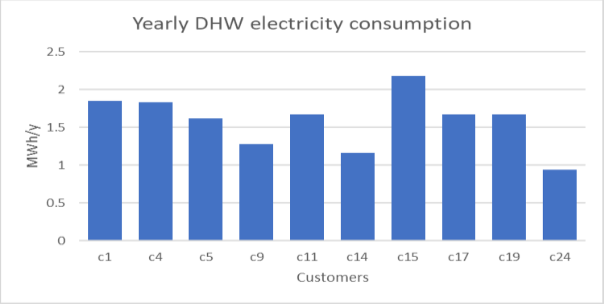

Figure 5: yearly DHW consumption

4.2 Technical performance parameters

The literature suggests several parameters to describe the technical performance of photovoltaic distributed generation in matching the demand. [10] The electricity self-consumed, defined as the difference between the photovoltaic production and the injection to the grid, is presented in equation 9:

$$E_{sc}(t) = E_{pv}(t) - E_{inj}(t) \qquad (9)$$

The Self-Consumption Ratio SCR, shown in equation 10 is defined as the ratio between the electricity self-consumed and the total photovoltaic production. It measures the performance in not injecting excess electricity.

$$SCS = \frac{\sum_{i=1}^{n} E_{SC,i}}{\sum_{i=1}^{n} E_{pv}} \qquad (10)$$

The Self-Sufficiency ratio SSR, shown in equation 11, divides the self-consumption by the total electricity demand E_{dtot} . It measures the performance in not purchasing from the grid.

$$SSR = \frac{\sum_{i=1}^{n} E_{SC,i}}{\sum_{i=1}^{n} E_{dtot,i}} \qquad (11)$$

The two parameters are described in [11].

4.3 Savings on the electricity bill

The tariff applied to all the customers is the bi-hourly scheme, taken from EDP Tarifarios [12]. The contracted power is 6.9 kW, the peak hours are between 8:00 AM and 21:00 PM. Peak price is 0.2028, off peak price is 0.0969 €/kWh.

The cost of electricity can be calculated for the base case where SENSIBLE equipment is not installed, and for the case study. To calculate the total cost of electricity for each customer in the base case, the equation 12 is applied:

$$B_{std} = n \cdot CPP + \sum_{i=1}^{x} 0.0969 \cdot E_{dtot,i} + \sum_{j=1}^{y} 0.2028 \cdot E_{dtot,j} \qquad (12)$$

CPP is the contracted power price, n is the number of days, $E_{tot,i}$ is the electricity demand in off-peak hour i and $E_{dtot,j}$ is the electricity demand in peak hour j. The current case can be calculated with equation 13, that considers the electricity purchased from the grid.

$$B_{std} = n \cdot CPP + \sum_{i=1}^{x} 0.0969 \cdot E_{p,i} + \sum_{j=1}^{y} 0.2028 \cdot E_{p,j} \qquad (13)$$

From the two equations 12 and 13, the savings can be calculated from equation 14.

$$B_s = B_{std} - B_{sensible} \tag{14}$$

5 Matlab Model

To set up a realistic model of the HMS, customer 5 has been selected as reference due to the completeness of the data. A first simulation has been performed to check the representativeness of the model, so the time series of the photovoltaic generation has been used.

Table 1: First results of the validation of the model

Parameter	Values from the model	Values from timeseries
Total Electricity Purchase	2.82 MWh	3.11 MWh
Total Electricity Injection	0.70 MWh	0.66 MWh
Total WH charge	1.69 MWh	1.61 MWh
SSR	35 %	52 %
SCR	68 %	66 %

5.1 Irradiation forecast model

Satellite based data of the hourly irradiance of Valverde have been found in Copernicus Atmosphere Monitoring Service (CAMS). the Similarity Model can be applied to the irradiation data for the year 2018. The error of the model has been estimated using the RMSE (equation 15) between the forecast and the real values.

$$RMSE = \sqrt{\frac{\sum(GHI_f - GHI_e)^2}{96}} \tag{15}$$

The result is an average daily RMSE of 15.5 Wh/m^2, with 57.9 Wh/m^2 for the worst forecast. An overview is shown in Figure 6.

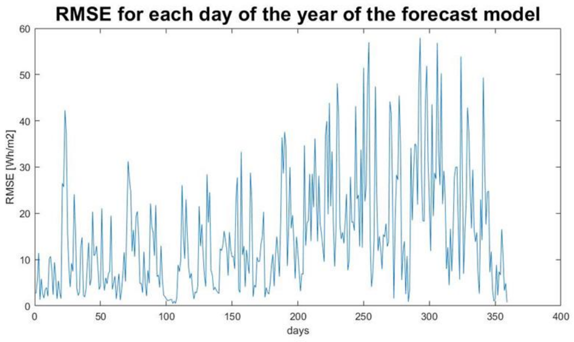

Figure 6: RMSE results of the forecast model

5.2 Photovoltaic generation model

To calculate the photovoltaic electricity production equation 16 can be used.

$$E_{pv} = I_T \cdot A_{pv} \cdot \mu_{module} \cdot \mu_T \cdot \mu_{dirt} \cdot \mu_{inv} \tag{16}$$

A summary of the parameters is presented in Table 2.

Table 2: Photovoltaic model parameters

Symbol	Name	Value
$\boldsymbol{I_T}$	Tilted irradiation	(from Perez)
$\boldsymbol{A_{pv}}$	Panel area	9.3 m^2
$\boldsymbol{\mu_{module}}$	Module efficiency	16.1 %
$\boldsymbol{\mu_T}$	Temperature efficiency	-0.39% / K
$\boldsymbol{\mu_{dirt}}$	Dirt factor	98%
$\boldsymbol{\mu_{inv}}$	Inverter Euro Efficiency	96.1%
$\boldsymbol{NOCT}$	Normal Operating Cell T	46°C

The cell temperature is given by equation 17.

$$T_{cell} = T_{amb} + \left(\frac{NOCT - 20}{0.8}\right) G \tag{17}$$

Where G is the irradiance in kW. The yearly production generated by the model is 2.3 MWh/y, in line with the values measured.

5.3 Water Heater model

The model keeps into account thermal losses, average water consumption profile, temperature thresholds: from 40 to 50 °C mainly with the electricity from the grid, from 50 to 53°C with pv and dimmer. The energy balance of the water heater is given by equation 18.

$$E_{wh,el} = \frac{V_{H20} \cdot \rho_{H20} \cdot c_{H20}\,(T_{max} - T_{inlet})}{3600}\,[Wh_{el}] \tag{18}$$

Due to stratification phenomena and different condition of mixing of the water in the tank, the effective mass of water heated up is very variable. The model has been tuned empirically by crossing temperature profile and electricity input, considering different capacities for static (thermal losses) and dynamic warm ups (water consumption). A randomization script generates a thermal load with a weighted probability in specific hours, based on the observation of the data of water consumption, refer Figure 7.

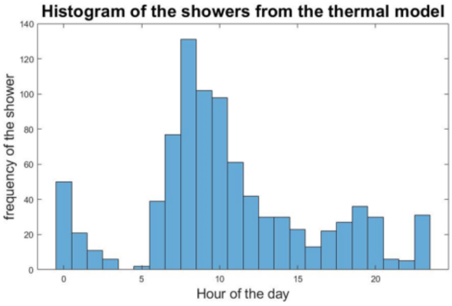

Figure 7: histogram of the frequencies of the hours when water consumption occurs

The model produces a yearly thermal load of 1.69 MWh_{el}, while the value from the time series is 1.66 MWh_{el} (ratio: 101.9%).

6 Results

The results are divided in two sections: the analysis of the performance and the results from the model

6.1 Technical performance results

The average SCR is 57.23 %. The value results particularly big for the customers that have a huge electricity consumption, or that consumes most of the electricity during the daytime, for instance customer 10. The highest SCR is achieved by the configuration that includes the battery. The average SSR of the customers is 31.16%. the best performance in terms of SSR is achieved by the small consumers.

Considering the two parameters together, shown in Figure 8, some conclusions are possible.

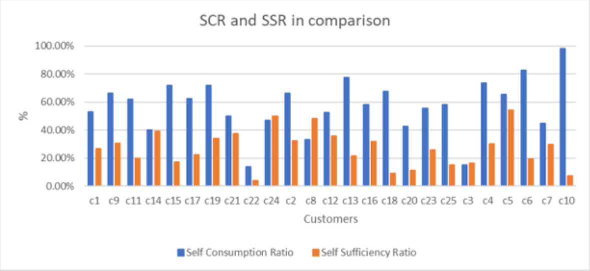

Figure 8: SCR and SSR in comparison

- High SCR and low SSR: the system is probably undersized.
- Low SCR and high SSR: the system is probably oversized.
- High SCR and SSR: the customer the system has a very high performance and it's properly sized.
- Low SCR and SSR: the performance is poor, the consumption might be shifted during night time. The battery could be undersized.

An example of the last case is customer 3, having 75% of the consumption during night hours.

6.2 Economic performance results

The average savings are estimated to be 352 €/y for each customer, corresponding to an average saving of 29 €/month. The estimation by EDP is around 25 €/month. [13] Clustering the customers according to the configuration, the best performing system is the one including the battery, as shown in Figure 9.

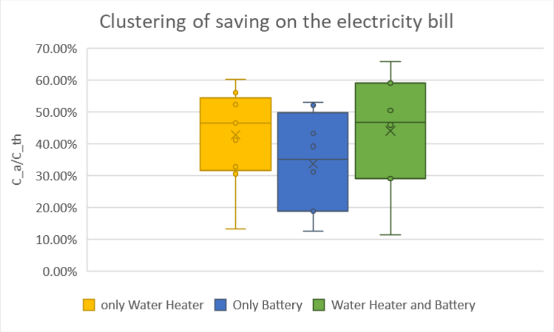

Figure 9: relative savings on the electricity bill according to the configuration installed

6.3 Matlab simulation results

The implementation of the new algorithm for the HMS follows the scheme presented in Figure 10.

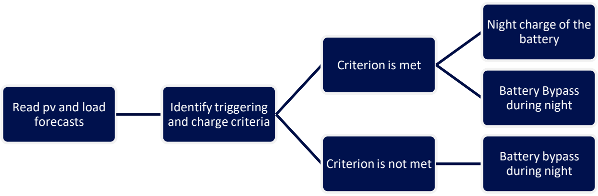

Figure 10: Scheme of the new HMS working principle

The general idea is to trigger some night charges of the battery, to take advantage of the cheaper electricity price. First the user decides a triggering criterion of activation, starting from the weather and load forecasts. Then a charging criterion for the battery is set, to decide how much of the capacity of the battery should be recharged for every activation. The algorithm verifies the triggering criterion every day at midnight: when the criterion is met, the battery is charged up to the desired capacity with the electricity coming from the grid. Several strategies of triggering and charge criteria have been tested. The main triggering criteria used has been to compare the photovoltaic generation forecast with the load forecast. If the daily load forecast is higher than the daily photovoltaic generation forecast, the algorithm charges the battery during the night of a specific percentage set in advance.

The final results are not bringing improvements to the original algorithm. The standard case (original algorithm) shows a better performance than the other attempts.

7 Conclusions

7.1 Financial perspectives

The financial inputs are presented in Table 3. The interest rate suggested by EDP for the calculations is 6%, and the lifetime considered for the project is assumed to be 20 years. The savings on the electricity bill are considered positive values in the cash flow calculation.

Table 3: Financial inputs

Device	CAPEX [€]	OPEX [€/y]	Lifespan [y]
Photovoltaic panel and inverter	1500	20	20
Smart Water Heater	800	-	20
Battery	2550	10	10
Battery inverter	500		20

Two cases can be analysed: with and without the battery. The savings are assumed 350 €/year, value taken from the average of the customers, plus the average savings due to the battery, around 77 €/year on average.

For a customer without the battery the NPV is 1374 €, the payback time is in year 9 while the IRR is 14.7%. The cash flows can be seen in Figure 11.

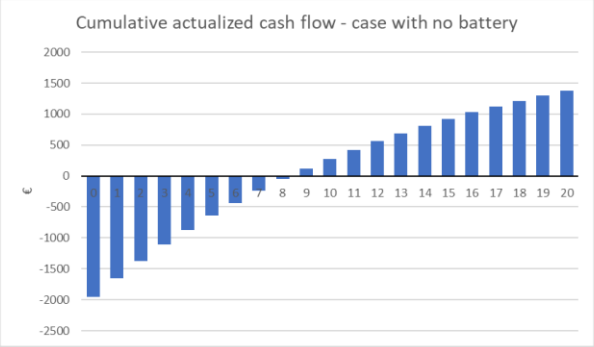

Figure 11: Cumulative cash flow, case with no battery

In the case with battery, the NPV is negative and also the IRR, with a value of -0.85%. The investment is not financially sustainable at the moment with the current prices of the batteries in Portugal (>750 €/kWh) while it would be starting from 340 €/kWh.

7.2 Carbon Footprint

The carbon intensity of the electricity production can be defined with equation 19:

$$CI = \frac{GHG_e}{E_{gen}} \tag{19}$$

Where GHG_e is the total emission of greenhouse gasses, expressed in tons of CO_2 equivalent, E_{gen} is the total electricity generated. The carbon intensity of the national grid of Portugal can be assumed to be 400 g $CO_{2,\ eq}$/kWh consumed by the end customer. [14] A similar value is found in [15].

The electricity self-consumed by the customers of Valverde totals 27134.97 kWh, corresponding to a reduction of the emissions of 10.85 tonnes of CO_2 equivalent. This calculation doesn't consider the emissions related to the installation and maintenance of the system and to the manufacturing of the components.

7.3 Socioeconomic impact

Distributed generation in general gives positive impact to the management of the grid. For instance, a reduction of the losses, improved reliability of the grid by reducing power flows, more free capacity available on the power lines, an increased renewable penetration in the domestic energy consumption. [16] Having a high number of customers getting more and more independent from the grid is expected to lead to a reduction in the earnings of the DSO. Nevertheless, the grid will still be needed to supply the customers when renewables are not available, and grid costs have to be recovered by the DSO. More customers are expected to become prosumers in the next future, increasing the renewable penetration in areas where the consumption is low. The combination of the two aspects is expected to considerably increase the grid costs and consequently the tariffs charged on the end customers. The most affected customers in this scenario would be the ones that cannot afford to install a solar system, generating an iniquitous trend in which the low-income households are disadvantaged.

An evolution of the current business model is expected to happen to mitigate this phenomenon. In fact, in a tariff where the customers are charged mostly on volumetric basis [€/kWh], customers having photovoltaic systems or in general private electricity generation would pay less than the customers totally dependent from the grid. [17] If grid tariffs are applied mostly on contracted power basis [€/(kWh d)] then the costs would be redistributed in a more fair and balanced way.

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